Modeling and design of an architecture for Adaptive Intelligent Educational Distributed CBR system

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Abstract— Nowadays E-learning systems have known notable progress in term of learning adaptation. Several systems were proposed in this context and different methods were adopted for the generation of customized learning paths. CBR is a problem-solving paradigm that is distracting increasing attention in the field of systems' personalization in various domains including E-learning, for the set of advantages that it provides as a decision-making tool in complex and unstructured environments, in addition to its capacity of reasoning in non-well described domains. In this regard, we present in this paper different CBR systems treating static and dynamic cases in the e-learning domain, and we propose, an architecture of an Adaptive Intelligent Educational Distributed CBR system that adopts a Dynamic CBR cycle for personalized pedagogical training generation, using Multi-Agent System to reduce system's complexity, and it defined various ontologies providing a detailed description of knowledge and serving it reuse and sharing. We also present the implementation of the proposed architecture by introducing the system's Technical Architecture and a scenario illustrating the system's functioning for learning process generation.

Index Terms— Case-Based Reasoning (CBR), Adaptive E-learning systems, E-learning, Ontologies, Multi-Agent System.

INTRODUCTION

Recently, Case-Based Reasoning had been growing impressively. Today, there are more than one hundred CBR systems reported in the literature. This technique had been adopted by different systems in diverse domains because of its approved efficiency as a decision-making technique and of its flexibility where it can be adapted to environment needs. Furthermore, CBR presents a set of advantages in term of knowledge acquisition, the capacity of reasoning in a non-fully described domain, clear presentation of system's new requisite, and that what make of it a good choice for different systems.

However, CBR is not a ready solution to use, Cases and reasoning are different from an application to another. There is, in fact, some conditions to be respected for an efficient CBR system. Generally, its construction consists basically of Case representation, Case indexation to facilitate the retrieving operation, Similarity definition between target and source cases, and the integration of the CBR in the needed system or organization.

In this context, an incomparable work had been carried by e-learning systems in term of personalizing the delivered content to the learner in order to customize learning style to each learner, as well as allowing him to interact with the largest community of practitioners and teachers, with the aim to improve learner's competencies. For that purpose, Adaptive e-learning systems make use of different decision making and knowledge management methods.

However, and despite the pedagogical and technological advances, current systems are far from being able to meet the expectations of educational actors in general and the concerns of the professionals training' in particular. Thus, our proposal comes to find a solution to the limitations faced by current Adaptive E-learning systems. We propose an Adaptive Intelligent Skills-Oriented and distributed E-learning System, adopting a dynamic cycle of CBR to generate a suitable pedagogical training and to manage the dynamic behavior of the learners, this cycle is integrated in a Multi-Agent System, to reduce its complexity and to ensure its extensibility. Otherwise, the system gets served by Semantic Web functionalities (Designing various ontologies) in order to improve the quality of services by providing a clear description of domain knowledge and by allowing the reuse and the sharing of this knowledge.

This article is organized as follows: in section II we present definition of the Case-Based Reasoning paradigm, in section III we give an overview of different adaptive e-learning CBR systems for the treatment of static and dynamic situations, in section IV we propose a basic architecture for an Adaptive Educational Distributed CBR, in section V we propose the system's implementation by introducing the technical architecture and functioning scenario. Finally, we draw some conclusions and perspectives in section VI.

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CASE-BASED REASONING PARADIGM

Case-Based Reasoning is an Artificial Intelligence approach adopted by several systems in a wide range of domains ([1], [2], [3]) as a solution to the adaptation problem. This paradigm shows significant promise for improving the effectiveness of complex and unstructured decision-making. The goal of the CBR approach is to solve a current target problem called "target case" by using a similar solved problem stored in the case base and called "source problem" and its solution "source solution". The pairs (source_problem, source_solution) are called "source cases" and the set of source cases is called "Case Base". We can distinguish to types of CBR systems:

- **CBR for static situations:** It's the first model adopted in the advent of CBR systems. These applications consist of having a full description of the characteristics of the target case before the beginning of the cycle. In these systems, cases must be indexed so that the retrieval step can use a structure to have access to cases.
- **CBR for dynamic situations:** The applications of reasoning based on cases dealing with dynamic situations are characterized by the fact of dealing with temporal target cases. These systems carry out a search for the best cases based on a similarity between historical.

This resolution process can be modeled by a static cycle of five phases [4] based on a knowledge base of the field of application :

- **Elaborate:** This phase has for role to reformulate a clear description of the target case from the submitted request, by putting in place different mechanisms to move from an often poorly expressed problem to a well-defined problem.
- **Retrieve:** Consists of extracting similar cases to the description of the problem to solve. This phase represents the starting point of the CBR cycle, it is a mandatory step because it facilitates the matching of the target problem to the equivalent existing source cases and helps to direct it towards an adaptable solution.
- **Reuse:** This phase has for role to select the adequate case for the target case from the retrieved cases on the basis of similarity measurement methods to reuse it as a solution. The achievement of these tasks is essentially dependent on the case structure, their indexation and the organization of the case base.
- **Revise:** Having mapped an adequate solution for the current case, this phase consists to evaluate the proposed solution in the real world. Therefore, the chosen solution will be examined by the user, an expert of the domain or automatically by the system. So it can be: accepted, corrected or rejected.

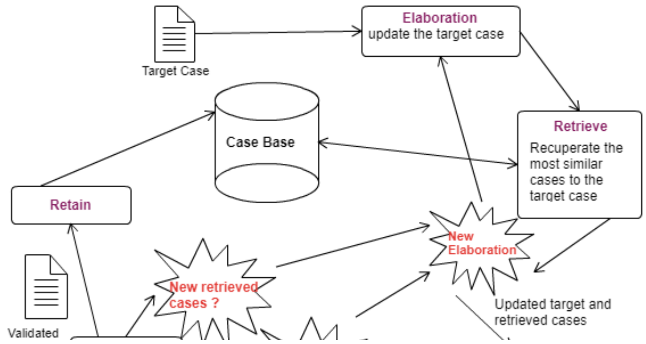

Figure 1: Dynamic CBR Cycle

- **Retain:** After the solution has been successfully adapted to the target situation. The CBR cycle consists of this phase to store the final solution as a new case for future use. This final step allows: to improve the experience of the system and to enrich the knowledge base.

Otherwise for the treatment of dynamic situation, [5] has proposed a dynamic cycle adapted to the continuous update of the situations. This cycle does not give importance to the order of the steps where it can be stopped and reloaded for any important change in the target situation as shown in figure 1:

EDUCATIONAL ADAPTIVE E-LEARNING SYSTEMS

E-learning systems are drawing more and more attention to personalizing the delivered content, and that. On the one hand, improve the quality of learning and minimize its cost. On the other hand, give a new form to the teaching-learning process by providing students an intelligent and interactive learning environment, without space-time constraints. Therefore, the use of CBR approach as a method for the prediction and adaptation of pedagogical content will widely help to create an interactive environment that cooperatively helps the learner in his various tasks while ensuring the providing of a tailored learning process to learner's needs.

However, despite the advantages provided by the CBR paradigm for problems solving and decision-making at complex and instructed environments. Researches for CBR in e-learning domain still limited.

In fact, the majority of work done in the e-learning domain for CBR was for the treatment of static situations. We cite among the existing Educational Systems adopting CBR for static cases:
[6] MOOC-Rec is an Adaptive E-learning System for the recommendation of appropriate MOOCs that greatly fit

learner's personal interests by responding to a specific request of a learner. MOOC-Rec applies the CBR approach to provide adequate pedagogical content. The cases to be treated are created by extracting learning source features from XML pages of MOOCs already indexed and listed in certain online directories dedicated to MOOCs, these cases are represented in a flat form by a set of pairs (Problem (user's query), Solution (MOOCs' URL)). Additionally, to simplify the retrieving task and reduce the retrieval time, the organization of cases in MOOC-Rec is based on similarities between cases, in the form the k-d binary tree that split the case base into groups of similar cases according to a given similarity measure. And as similarity function, MOOC-Rec adopts the Levenshtein distance to measure the local similarity between cases' attributes. Furthermore, for more efficient similar cases selection, the retrieval algorithm computes similarity bounds to determine which groups of cases should be considered first. [7] an intelligent speech-enabled E-learning application builds to offer a personalized distance learning for students with physical disabilities (visually-impaired learners), providing a dual interface (Voice User Interface and Web User Interface). this system adopts CBR for the treatment of learners' queries in order to provide adequate responses to their questions and learning goals, it integrates, in addition, the Porter stemming algorithm with CBR to improve the retrieving of existing similar cases task. And [8] This research proposed a personalized curriculum generation approach by employing Genetic Algorithm (GA) and CBR to construct an optimal learning path for each learner. In this work, CBR has for role the personalization of the knowledge database and the analysis of summative assessment results. For this system a new case for the CBR treatment signify that the learner fails to reach the mastery level in his current unit, in such case, the CBR cycle will be triggered for the analysis of the assessment results and to provide corrective activities for that specific case. The treated cases are represented by a list of descriptors in the form of pairs (Attribute, Value). For the retrieving phase, the system makes use of knowledge guide method to guide the new case to a feature similarity group, and the Weight Ratio Functionality (WRF) method to measure the similarity between source and target cases. We cite in addition [9] Pixed (Project Integrating experience in Distance Learning) is a case-based reasoning system attempting to use learners' interaction logs gathered as learning episodes to provide contextual help for learners trying to navigate their way through an ontology-based Intelligent Tutoring System (ITS). In addition to providing them with an adapted link structure for the course. The CBR is triggered in this system when a learner asks for some assistance during the learning process. Cases in Pixed are in the form of learning episodes gathering various information within a vector grouped in three parts: the system situation at the beginning of the episode, the actions performed by the learner, and the system situation at the end of the episode. For the retrieval of best similar source cases that fit learner's needs, Pixed uses the classical similarity approach of Tversky [10] by using a set of similarities and dissimilarities according to the specificities of a learning episode features. And [11] a Question and Answers (Q&A) system proposing integration of GA-based CBR into the traditional Q&A system to put forward an interactive Q&A engine in order to generate more accurate and consistent solutions. The system has been used in realistic situations, a professional e-learning site of Shanghai Jiao Tong University. It aims at solving the problems faced by the students during their learning process. The main function of the system is to analysis learners' submitted questions automatically and find the probably answers to the users. For the achievement of the retrieving task, its proposes Overall Similarity Degree (OSD) method for similarity measurement, which is derived by summing each degree of similarity resulting from comparing each pair of the corresponding case features out of the selected training case and old case. Cases are all stored in one case base containing both training cases and old cases. We cite as well [12] Q&A (Questions and Answers) system is an open adaptive framework providing an intelligent distance-learning environment, which is developed and used at the Network Education College of Shanghai Jiao Tong University. The motivation of this work is to build a new distance learning system that enables students to conduct online studies easily according to their own educational backgrounds and study habits. The system allows learners to pose questions to a virtual teacher interactively, during a class session. Therefore, the use of CBR has for goal to provide adequate answers to learners' questions during the pedagogical training. Cases in this domain are the pairs of questions and their corresponding answers that students and teachers have used in the past. Otherwise, the current question provides keywords that trigger the CBR cycle in order to find the relevant answers. For the retrieving of similar existing cases, Q&A system makes use of Term Frequency–Inverse Document Frequency (TF-IDF) as similarity measurement function.

Yet, only few works had been carried out in E-learning domain for CBR systems dealing with dynamic cases. According to our research, we have found two E-learning systems using CBR for dynamic situations.

IDCBR-MAS [5] a Distributed Dynamic CBR system for dynamic cases ensuring a continuous follow of the learner during the learning process. IDCBRMAS adopts the multi-agent approach to implement the dynamic CBR cycle. This system had been applied on an intelligent tutoring system as a solution for the learning adaptation problem, using learner's traces resulting from learner's interaction with the Moodle platform as a knowledge source for the adaptation procedure. It proposes a dynamic CBR cycle to manage the dynamic behavior of the learners on the platform. It also proposes the ILCSS method for similarity measurement based on the Longest Common Subsequence (LCSS) algorithm for better matching between the target and the source cases. Cases in IDCBR-MAS are represented by a collection of semantic features in the form of triplet (Object, (Qualification, Value)), these cases are stored in a hierarchical case base of two levels: low level that is a flat memory containing similar case groups and a high level containing indexes representing the common characteristics of a group of similar cases stored in the low level. IDCBR-MAS has a multi-layered architecture managing by a set of agents acting in a collaborative way in order to accomplish the dynamic CBR cycle adequately and to provide the most adapted pedagogical content to learner profile.

Mobile Agent E-learning System [13]: An adaptive multi-agent educational system adopting the CBR approach as a solution for the adaptation task. This architecture gives users the ability to collect, share, distribute and reuse e-learning knowledge from heterogeneous knowledge bases. The model is employing CBR method to provide personalized pedagogical content based on the similar previous situation. The system adopts a static CBR cycle for the treatment of dynamic situations (learner profile), it considers the updated learners' profiles as new target profiles. Moreover, this system provides heterogeneous knowledge sources to describe learners' needs preferences and goals (learner profile modeling) and gives a detailed description of pedagogical resources (learning resources modeling). The CBR cycle is triggered in this system when a new profile is created or the current is updated. Otherwise, for similar cases retrieving the Mobile Agent E-learning System employs the Nearest Neighbor (NN) matching function.

We illustrate below two comparative tables (table I and table II) of the static and dynamic Case-Based Reasoning system mentioned above. The comparison is based on system type (Static or Dynamic), methods of similarity measurement for the matching of similar stored cases to the target case, case representation, in addition to the CBR cycle by comparing the different phases of the reasoning cycle (Retrieve, Adaptation, Revision and Retain).

LIMITS OF THE EXISTENT

Having for aim to enhance the efficiency of distance learning and to provide learners with the relevant learning process according to their needs and their preferences, several works had been carried out for e-learning CBR systems. For that purpose, the existing systems had adopted different methods for the implementation of the CBR cycle in order to achieve the best solutions for learners' educational problems.

TABLE I:
COMPARATIVE TABLE OF MENTIONED STATIC CBR SYSTEMS

	Similarity Measure	**Case Representation**	**Retrieve**	**Adaptation**	**Revision**	**Retain**
MOOC-Rec	Levenshtein distance for local similarity	List of descriptors (Attribute, Value)	Unidimensional search	Null Adaptation (use the proposed case without any modification)	No	Automatic new case saving
Intelligent Speech-Enabled E-Learning System	Porter Stemming Algorithm	—	Unidimensional search	Null Adaptation	No	Automatic new case saving
E-learning System based on Genetic algorithm and Case-Based Reasoning approach	Weight Ratio Functionality (WRF)	List of descriptors (Attribute, Value)	Multidimensional search	Transformational Adaptation	Yes	Automatic new case saving
Project Integrating experience in Distance Learning	Tversky similarity approach	List of Vectors	Unidimensional search	Transformational Adaptation	Yes	Automatic new case saving
GA based CBR approach in Q&A system	Overall Similarity Degree (OSD) method	List of descriptors (Attribute, Value)	Multidimensional search	Null Adaptation	Yes	Automatic new case saving
Data mining and Case-Based Reasoning for distance Learning (Q&A)	Term Frequency–Inverse Document Frequency (TF-IDF) method	List of descriptors (Attribute, Value)	Unidimensional search	Null Adaptation	No	Automatic new case saving

However, efforts made in this context are still limited in some areas such:

TABLE II:
COMPARATIVE TABLE OF MENTIONED DYNAMIC CBR SYSTEMS

	Similarity Measure	**Case Representation**	**Retrieve**	**Adaptation**	**Revision**	**Retain**
IDCBR-MAS	Inverse Longest Common Subsequence (ILCSS) method	List of triplet (Object, (Qualification, Value))	Multidimensional search	Transformational Adaptation	Yes	Automatic new case saving
Mobile Agent E-learning System	Nearest Neighbor (NN) matching function.	List of descriptors (Attribute, Value)	Multidimensional search	Null Adaptation	Yes	Automatic new case saving

A. Learner Real-time follow up

Adaptive e-learning systems have for goal to provide learners with customized pedagogical training, for that purpose they employ various methods to gather information about learners to identify their goals, needs, and preferences, such by recording their traces on the learning platforms. Nevertheless, most of the created e-learning CBR systems don't take into account the dynamic behavior of the learner, as for [7], [8], [9], [10], [12] and [13]. During a learning process, students' can define new training goals or they may have new needs, and that requires a continuous follow, guidance and assistance of learners during the learning process in order to help them to achieve their objectives. As a consequence, a static treatment will not assure an individualized real-time follow up of the students, which can affect the efficiency of the pedagogical training.

B. Treated Features

Adaptive e-learning CBR systems give prominence to knowledge gathering, in an explicit way by collecting information from forms and questionnaires delivered to the learner as for [13] or in an implicit way that consists of collecting information about learners through their navigation on the learning platform as for [8] and [9]. And that in order to provide the learning system, with the necessary information to be able to assign the learning objects most adapted to the characteristics of the learner by creating a learning path.

However, features describing the treated cases are of a limited number so they don't provide the system with a clear description of learners' goals, preferences, prerequisite, learning styles, and other useful information.

C. Pedagogical Content

The existing e-learning CBR systems investigate further in term of distance learning personalization. Yet, most of them neglect the pedagogical content structuring or the delivered learning resources quality which is a crucial element of the learning process, and that influence the efficiency of the educational training provided. Giving for example [6], [12] and [12] these systems are made to answer students' questions during the learning process about the learned materials in order to provide learners with assistance and help them in understanding the course that they choose to learn.

PROPOSED ARCHITECTURE

In order to provide learners with the proper pedagogical training in terms of competencies development through an adaptive e-learning system, we propose a basic architecture of an Adaptive Educational Distributed CBR system based on various approaches:

- Multi-Agent Approach: This paradigm provides an appropriate architecture for the design and implementation of adaptive educational systems, as it regulates the increased complexity of the local problem-solving process required in such domains.
- Semantic-Web functionalities: Educational systems incorporates Semantic Web (SW) technologies in order to provide a more adaptable, personalized and intelligent learning environment. This incorporation is illustrated by the use of ontologies for knowledge description.
- Competence-Based Approach: The Competence-Based approach seeks to develop learners' acting ability in order to make them capable to use their required knowledge for solving real problem situation [14]. Therefore, it contextualizes learning and allows learners to share, exchange and cooperate with each other during the various learning processes

As shown in figure 2, the designed architecture for Adaptive Educational Distributed CBR system (AEDCBRS), is composed of 9 agents collaborating to cover the different functionalities of the system. For the generation of personalized pedagogical training, we have employed the dynamic CBR cycle proposed by [5] managed by 6 agents ensuring the good functioning of the reasoning cycle:

- **Interface Agent (IA):** This agent acts as an intermediate between users and other agents in order to achieve learners' goals. It receives external requests from learners and conveys them to Manager Agent. those requests could be for registration, connection, profile editing, or pedagogical training request. It provides also an adaptive interface to users' needs and preferences.
- **Manager Agent (MA):** This agent ensures the proper functioning of the system, and assigns tasks to agents according to their roles. The Manager Agent determines the nature of the request coming from the Interface Agent and selects the appropriate agent to contribute to fulfilling the upcoming query. This agent receives later on the task result from the chosen agent and it sends it to (IA) in order to be displayed to the user.
- **Profile Manager Agent (PMA):** The role of this agent is to create, update, delete, search and store learner profile, following to Interface Agent request. It may also be requested by the Manager agent to get information about the learner, learning object, competencies and pedagogical training sequences in order to help Elaboration Agent to achieve his tasks properly.
- **Elaboration Agent (EA):** The Elaboration Agent provides a clear and brief description of the learner necessary information. Based on the information received from the (MA) about the current request and the target case in order to facilitate the search of similar source cases.
- **Retrieving Agent (RA):** The role of this agent is to make a search based on the criteria specified by the elaboration agent in addition to calculate the degree of similarity between the selected features and the existing ones stored in system's case base, using Data Mining method (Euclidean Distance) in order to filter the most similar ones.
- **Adaptation Agent (AdapA):** The adaptation agent receives the list of the retrieved source cases from (RA) and selects the most appropriate solution for the treated case.
- **Evaluation Agent (EvA):** This agent evaluates the proposed solution by sending it to the learner, that express his opinion about the provided training. If the proposed learning process had been judged sufficient, it will be saved by (RetA). Otherwise, the Evaluation Agent asks the Elaboration Agent to make a new elaboration based on learner's comments.
- **Retaining Agent (RetA):** The role of this agent is to store the current profile with the sufficient proposed solution in the system's case base as a new source case for later use.
- **Updater Agents (UA):** This agent ensures an appropriate functioning of the CBR cycle in case of profile or request updating. this agent is triggered by the Manager Agent to stop the CBR cycle, detect the important made changes and to inform the (EA) that a new elaboration of the target case is needed.

In order to simplify the adaptation process and to ensure the reuse and the sharing of information, we propose to organize the system's knowledge into various interoperable models, that satisfy the system's objectives. With this aim, we propose various models to be used by our Adaptive E-learning system:

- Learner Model: Or Learner Profile, provides a detailed description of the learner (goals, preferences, prerequisite, learning styles, competencies, …). This model can be designed on the basis of different standards as IEEE-PAPI [15] and LMS-LIP [16].
- Learning Object Model: This model provides a full description of the pedagogical content delivered to the learner. It helps in the improvement of the matching task between the learning object and learners' needs and preferences. Learning Resources modeling can be performed using Learning Object Meta-data (LOM) [17].
- Competencies Model: This model provides a detailed description of the competencies that a learner could improve by taking specific pedagogical training. Learner Competencies model can be designed by the use of IMS-RDCEO [18] standard.
- Pedagogical Training Model: This model provides a description of the different sequences of the learning object, in order to generate an adequate pedagogical training for a specific goal or for a particular competence to improve or to require. Pedagogical training model can be modeled using IMS-Learning-Design [19].

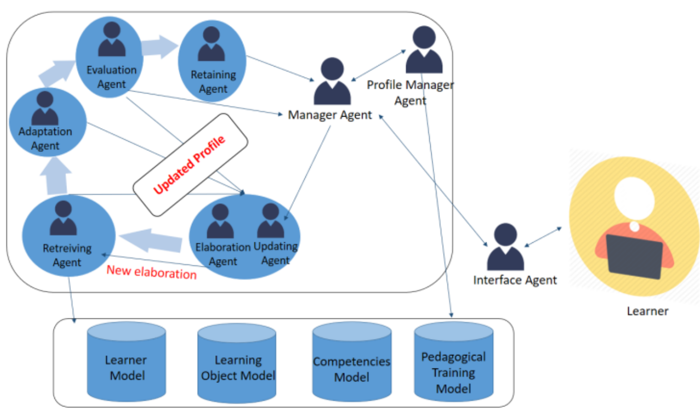

Figure 2: Architecture of AEDCBRS

REALIZATION

A. Technical Architecture

The initial test of our architecture was carried out on Eclipse under JAVA integrating JADE Framework http://jade.tilab.com/ to implement our Multi-Agent System. JADE is an open source platform providing a development environment for multi-agent systems reliable. It provides a comprehensive set of services and agents complying with the FIPA specifications for system interoperability. The communication between the agents is assured by ACL language defined by FIPA.

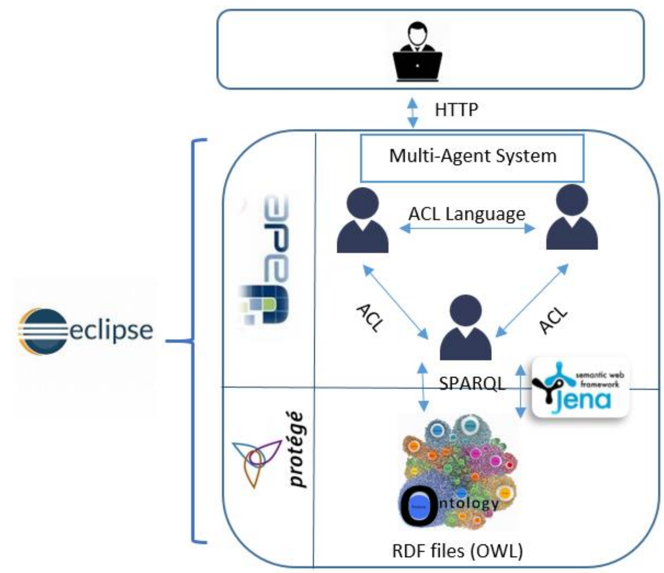

Figure 3: Technical Architecture

For the edition of the different ontologies, we chose to use among the existing software, Protégé 5.1.0 https://protege.stanford.edu/ , which is a free, open source ontology editor and a knowledge management system. Otherwise, for RDF files language we used OWL.

Apache Jena is an open source framework for JAVA for the building of Semantic Web and linked data applications http://jena.apache.org/ . It provides an ontology API for RDF, RDFS and OWL, SPARQL and includes a rule-based inference engine. The use of Apache Jena in our situation was for the assurance of a suitable communication between the Multi-Agent system and the created ontologies.

B. Functioning Scenario

The CBR cycle is fulfilled by a collaboration between different agents, to generate customized learning objects. For that, we presented above an illustrative scenario shown in figure 4 describing the functioning of the proposed architecture.

The system provides learners with an interface assuring a good communication with the system managed by an Interface Agent adopting a cyclic behaviour. Through this interface, learners are able to connect, register, update their profiles and make requests for pedagogical trainings. At any registration, learners are invited to pass the Felder and Silverman Learning Styles [20] test to identify their personal learning styles. In our case, learners' requests present their (objectives, prerequisite, level and the target competence to improve or to acquire).

After the request submission, Manager Agent collects the information provided by the executed query and extracts the rest of the information about the learner from Learner profile ontology (using getAttributes() method). Later then, it sends the gathered knowledge to Elaboration Agent. This agent selects the important features to be used in the similarity calculation from the received data, to provide the Retrieving Agent with a detailed but specific description of the treated case. (RA) calculates the Euclidean distance between the selected attributes from the target case and the same attributes of the source cases. As result this agent returns a list of the source cases having a distance smaller than the defined threshold and it sends it to the Adaptation Agent, that selects from the received list the nearest source case to the treated one (having the smallest distance), and it affects the solution used by the chosen stored case to our target case as the proposed pedagogical training to be taught. The suggested learning process is then sent to the Evaluation Agent. This agent sends the proposed training to the Manager Agent to be introduced to the learner. This latter evaluates the solution and sends his opinion about it to the (EvA). If it is judged sufficient, (EvA) sends the treated situation and the proposed solution to the Retaining Agent which is engaged of storing it in the case base for future use. Else (EvA) returns the proposed solution and learner's comments to the (EA) to provide a new elaboration.

In case if the learner makes changes on any of the features used in similarity measurement or it updates his request, the Updating Agent is triggered by the (MA) to stop the reasoning cycle and provide the (EA) by the new information to execute a new elaboration for the same learner profile.

C. Treated Situation

Learner profile is a very important component in our system, the set of information contained in this profile allows adapted learning to student's specificities. Based on IMS-LIP standards we proposed the model shown in figure 5, that contains in addition of IMS-LIP characteristics: Portfolio that resumes learners' experiences, Activity, Progression, and Achievement allowing us to follow learner's performance on the system and Learning Styles containing the result of Felder

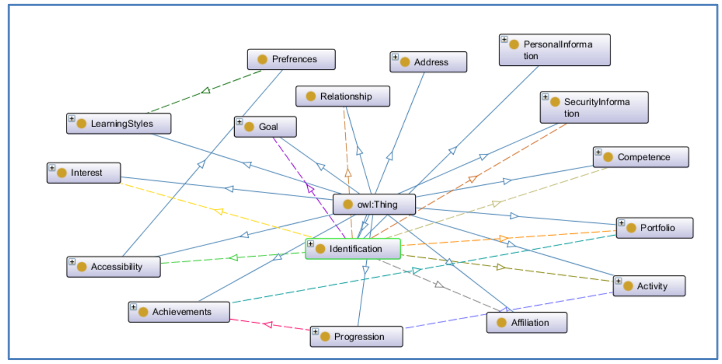

Figure 5: Learner Profile Ontology


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    <TechCompLevel rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Advancer</TechCompLevel>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#GoalL1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#GoalL1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Goal"/>
    <Learning rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Learn JAVA Programing</Learning>
</owl:NamedIndividual>
```


Figure 2: Example of case (Part 1)


```
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#InterestL1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#InterestL1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Interest"/>
    <InterestDescription rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Programing POO Computer Languages</InterestDescription>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Learner1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Learner1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#PersonalInformation"/>
    <Email rdf:datatype="http://www.w3.org/2001/XMLSchema#string">amrou.mouna@gmail.com</Email>
    <LearnerName rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Mouna Amrou</LearnerName>
    <Sexe rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Female</Sexe>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#LearningStyles1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#LearningStyles1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#LearningStyles"/>
    <ActifPercentage rdf:datatype="http://www.w3.org/2001/XMLSchema#string">50%</ActifPercentage>
    <GlobalPer rdf:datatype="http://www.w3.org/2001/XMLSchema#string">25%</GlobalPer>
    <SonsorialPercentage rdf:datatype="http://www.w3.org/2001/XMLSchema#string">25%</SonsorialPercentage>
    <reflexifPercentage rdf:datatype="http://www.w3.org/2001/XMLSchema#string">50%</reflexifPercentage>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#ProgressionL1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#ProgressionL1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Progression"/>
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</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Projet -->

<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Projet">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Portfolio"/>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#SILearner1 -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#SILearner1">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#SecurityInformation"/>
    <Password rdf:datatype="http://www.w3.org/2001/XMLSchema#string">MunaPassword</Password>
    <UserName rdf:datatype="http://www.w3.org/2001/XMLSchema#string">MunaAr</UserName>
</owl:NamedIndividual>
<!-- http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#formationUniversitaire -->
<owl:NamedIndividual rdf:about="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#formationUniversitaire">
    <rdf:type rdf:resource="http://www.semanticweb.org/soundouss/ontologies/2017/7/Learner#Portfolio"/>
    <Degree rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Master BioInformatics</Degree>
    <Period rdf:datatype="http://www.w3.org/2001/XMLSchema#string">2015-2017</Period>
    <University rdf:datatype="http://www.w3.org/2001/XMLSchema#string">ENSA Tangier</University>
</owl:NamedIndividual>
</rdf:RDF>
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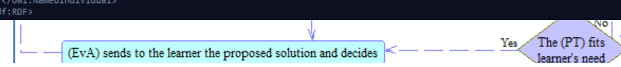

Figure 7: Example of case (Part I1)

Figure 4: System's Functioning Scenario

and Silverman test to determine learners learning styles.

- Example of a learner profile (target case):

Figure 6 and 7 present an OWL file of the learner profile, containing information about a learner.

CONCLUSION

The CBR approach shows a significant promise for improving the effectiveness of complex and unstructured decision making. Therefore, it can be an appropriate approach to aid in curriculum design dealing with the e-learning system environment. Despite proved efficiency, researches conducted on E-learning domain is still limited specially for the processing of dynamic cases.

For that, this article presented an overview of the Case-Based Reasoning paradigm, and different Adaptive Educational CBR systems for the treatment of static and dynamic situations, in addition of the different methods to be combined with this decision making tool in order to enhance the system's efficiency, reduce its complexity and ensure its extensibility. as for Multi-Agent paradigm and Semantic Web Services.

The proposed architecture and the achieved implementation are an initial conceive of the organization and the functioning of the Adaptive Intelligent Educational Distributed CBR system that we aim to develop.

We prospect improving the retrieving algorithm as to effectuate a multidimensional case retrieval, as we need to define a filtering method for Adaptation Agent allowing the selection of the best source cases from cases having the same distance, we look also to ameliorate the Interface provided as to offer more services and to be simpler for learner's use. Moreover, we also prospect improving the architecture to manage professors' activities in the system.

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